When the Tides Come, Where Will We Go?

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When the Tides Come, Where Will We Go?
Modeling the Impacts of Sea-level Rise on Greater Boston's Transport and Land Use System

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ABSTRACT

For coastal urban areas, increased flooding events pose one of the clearest climate change threats. We demonstrate how a land use-transport (LUT) model can be used to forecast the short and longer term impacts of potential 4-foot sea level rise in Greater Boston by 2030. The short-term scenario represents the immediate transport system response to inundation, which provides a measure of resiliency in the case of an extreme event, such as a storm surge. In the short run, the results reveal that transit captive users will suffer more. Transit, in general, displays less resiliency, at least in part due to the center city's vulnerability and Boston's radial-focused transit system. Trip distances would modestly decrease, and average travel speeds would go down by over 50%. Rail transit ridership would be decimated and overall transit usage would go down by 66%. The longer term scenario aims to predict how households and firms would prefer to relocate in the "new equilibrium" where over ten square miles of land disappear and the transport network inundations become permanent. Assuming no supply constraints, new residential growth centers would emerge on the peripheries of the inundated zones, primarily in the inner-core suburbs. Some regional urban centers and traditional industrial towns would boom. Firms would be hit harder, due to their heavy concentration in the inner-core; firm relocation would largely follow households. Transit usage would again be decimated, but walking trips would increase. Results, however, should be viewed as cautious speculation.

INTRODUCTION

The world now largely recognizes that the global climate is warming, likely bringing a host of consequences which will vary widely by region. Ongoing efforts at emissions mitigation are necessary, but adaptation actions are now nearly inevitable. For coastal urban areas, increased flooding events pose one of the clearest threats. Rising sea levels coupled with increased precipitation and more intense and frequent extreme weather events, such as hurricanes, point to the need for planning for flooding and possible long-term needs for major resettlement.

Storms like 2012's Hurricane Sandy dramatically demonstrated the potential short-term consequences in terms of massive disruptions to susceptible infrastructures (e.g., New York City's public transit system) and major dislocations to residents and businesses. The immediate response has primarily been to "retrench" and "rebuild," essentially a "robustness" posture: strength and sturdiness in the face of uncertainty. The long-term perspective, however, arguably requires a more "resilient" posture, a flexible system that can more easily adapt to the high degrees of uncertainty associated with long term-changes (e.g., sea level rise) in light of long-term investment decisions (e.g., infrastructure and housing locations).

Researchers and policymakers have focused on urban land use as a potential transportation energy reduction strategy well before climate change mitigation was a concern (e.g., *1*). Using simulation tools for understanding the potentials dates to around the same time (*2*). In more recent decades, numerous studies have used increasingly sophisticated land use-transport (LUT) models to examine the possibilities for mitigating transportation greenhouse gas emissions by changing urban growth patterns (e.g., *3*). Less work, however, has focused on using these tools to better understand the adaptation side. That is, how might, or how should, the LUT system respond and adapt to the climate change threat, in the short and longer-terms?

This paper provides an initial exploration of possible answers to these questions with an LUT model developed for Greater Boston, using commercial software. Our purpose is to demonstrate how such tools might be used to assess possible tradeoffs and develop better resiliency plans. For example, might land use strategies consistent with transportation emissions mitigation (e.g., "smart growth") be inconsistent with adaptation, if the former implies densification in at-risk areas? Which transportation infrastructures are most likely to be adversely affected and what might be the long-term impacts on location choices? Where might dislocated residents and businesses prefer to relocate and how might we start such resiliency planning taking these preferences into account?

In exploring how LUT models might help answer such questions, this research is necessarily and entirely speculative. None of us should "believe" predictions 30 or 50 years into the future using models estimated on and calibrated for today's reality. This is especially the case when trying to predict impacts of exogenous forces as uncertain as climate change, which imply unprecedented long-run losses of transportation and real estate assets, while assuming technologies and behavioral preferences remain static. Our models are not "official" models, nor do they represent "official" forecasts. Our intention is demonstration.

PRECEDENTS

An increasing amount of research aims to predict and analyze the effects of inundation events or other climate change-related disturbances on transportation (e.g., *4*; *5*). Most research on sea level rise (SLR) and flooding locates and quantifies impacts, using GIS and LIDAR data to determine the extent of threatened assets and including detailed information on soil conditions, road grade, drainage, etc. (e.g., *6*). Though often focused on impacts to road networks, some also focus on transit infrastructure (*7*).

Transport network vulnerability studies became increasingly common in the mid-1990s, after the Kobe earthquake (*8*). Related methods soon thereafter began being applied to network disruptions due to climate change risks. Such disruptions can be modeled in many different ways. Lu & Peng (*8*) provide a detailed review; here we focus on those related specifically to climate change-related inundation risks, primarily at the urban level. Suarez et al. (*9*), examining the Boston case, used a regional travel model and measured the impact as the number of trips lost due to SLR and the estimated cost of increased travel time and lost trips, under different exogenous population and land use patterns. Their target outputs identified the number of trips that would not occur due to flooding of the origin or the destination zone or the necessary transportation infrastructure. Some of the trips still occurring will take much more time. They assumed that commuting trips to a flooded area do not occur, all trips from flooded residential areas do not occur, and shopping trips redirect to the nearest other shopping area. They consider a network link non-usable if touched by an inundation layer. A direct empirical and methodological precedent for our work, Suarez et al (*9*) only model the road network (i.e., they ignore transit), analyze a small network (less than 10% of all links in the region), and treat land uses exogenously.

Chang et al. (*10*) used a similar method in analyzing network impacts under flooding conditions in Portland, Oregon. They used hydrological models, a framework for identifying "critical" linkages in the region, and the MPO's transport model to compute changes in vehicle hours traveled (VHT) and vehicle distances traveled (VDT). They found minimum impact on these measures, although the flooding extent modeled was constrained to two river watersheds, with relatively small regional impacts. Transit impacts were excluded. Lu & Peng (*8*) examined network and zonal vulnerability under two different SLR scenarios in south Miami, utilizing accessibility changes estimated from a model of 130 traffic analysis zones (TAZs). They did not include transit system impacts nor subsequent changes in land uses. Finally, Cambridge Systematics (*5*) inventoried New Jersey's transportation assets and identified the vulnerability or resiliency of critical assets under climate change scenarios. GIS layers represented areas at risk and a four step travel model was used to compute zonal criticality scores based on highway assignment and the number of persons and jobs in a given TAZ. The approach was used to identify critical road network links (with high traffic and connecting "important" zones).

We could find no examples of efforts to examine long-term metropolitan-level vulnerabilities to inundation using LUT models. But, such models may provide useful insights. In the case of an acute incident, such as a major storm surge, a travel network model can provide indications of areas of immediate risk and dynamic traffic assignment can show the degree of network resiliency. But such analyses ignore longer term reactions. For example, if flooding recurs with increasing regularity, the land market will react, in part due to the habitually degraded transport performance. At the long-term extreme, if permanent inundation occurs, knocking out transportation infrastructures and large habitable areas in a metropolis, where might people and firms want to go? The next section presents the method we use to help begin answering some of these questions.

METHODS AND DATA

Model Platform

We developed an integrated LUT model for Boston metropolitan region (MIT-LUT), based on Cube Voyager and Cube Land software and Python scripting. The MIT-LUT model has the same spatial extent as the Central Transportation Planning Staff (CTPS)'s transport model, with 986 TAZs in the transport model and 2727 TAZs in the land model.

Cube Land is the commercial version of MUSSA, an operational land use model based on auction theory (*11*). It consists of three interdependent models, demand, supply and rent, to determine market equilibrium. In the demand model, a consumer decides the bid for each type of property in each zone. The bid or willingness to pay, comes from the utility function, which depends on the consumer characteristics, real estate attributes and location. Given fixed supply, the highest bidder wins. In the supply model, supply agents decide the amount of each type of real estate to offer based on profit maximization. Rent connects supply and demand. The auction process adjusts rents and bids until all agents are located without incentive to move.

The MIT-LUT model allocates 12 types of households (defined by age, income, size), and 11 types of firms (defined by industry) to 12 kinds of real estate units (e.g., single family, large apartment) in each TAZ. We estimated household and firm location choice models using the 2010-2011 Massachusetts Travel Survey (2010MTS), InfoGroup data, MAPC/MassGIS parcel data, and Census data. The household location choice model has a rich representation of zonal attributes, such as accessibilities to jobs and shopping, race, SAT scores, income, crime, FAR, and taxes, and household characteristics including size, age, income, student, children etc. The firm location choice model includes variables such as distance to highway entries, accessibility to population and employment, density, job density by sectors, FAR etc. We calibrated the land model for 2010.

The transport model is a four-step model with a vehicle ownership module added. We characterize households into 224 types, based on size, workers, income and vehicle ownership. Trip distribution is done in a disaggregated manner by five worker earning groups. The vehicle ownership model and mode choice model have the logit choice structure, estimated using 2010MTS. Five modes are specified: single-occupant vehicle (SOV), auto-passenger (APAX), walk-access-transit (WAT), drive-access-transit (DAT), and walk (WALK). Trip purposes include Home-based Work (HBW), Home-Base Shopping (HBSH), Home-Based School (HBS), Home-Based Other (HBO), Non-Home-Based Work (NHBW), and Non-Home-Based Other (NHBO). The transport model is estimated and calibrated for year 2010.

The land and transport models are linked by accessibility measures, household and firm locations, and other zonal variables derived from number of agents and travel skims, updated during each model iteration.

Sea Level Rise Scenario

SLR data, in GIS format, come from the National Oceanic and Atmospheric Administration (NOAA)'s website (https://coast.noaa.gov/slrdata/). NOAA created these layers using a "modified bathtub" model, a digital elevation model of the region's land overlaid with data on the elevation and extent of water. Local and regional data on water features along US coastlines and the connectivity of other hydrological features are considered; areas of non-coastal land adjacent to coastal land can be inundated via water flow.

NOAA provides one- to six-feet SLR layers. We chose to model the four-feet scenario, since it marks an inflection point, the point of the greatest change of slope in terms of impacts on transportation assets and land uses, such as inundated rail and bus stops, and lost jobs and households (*12*). We used GIS tools to intersect SLR4ft layer with the TAZ shape-file of our model area. Four-feet SLR, inundates (in 2010): 279 TAZs, or about 10.3 square miles; 4% of population and households; 5% of jobs; four subway stations (Aquarium, Orient Heights and

Revere Beach on Blue Line, and Kendall/MIT station on Red Line); 2.2 miles of the Red Line and 2.1 miles of Blue Line; the Chelsea Commuter rail station is inundated; 2% bus stops and 24% of bus routes; and 356 out of 24577 road miles (*12*) (Figure 1).

Network Inundation Methods

Dowd (*12*) details the strategy used for degrading conditions on the link. Inundated links remain in the network, but with link attributes such that the travel time is too long for the link to be used. The predicted level of water on a link determines if a link is degraded or disabled. A degraded link is still usable by vehicles (including buses) and persons, but not by rail vehicles. Disabled links are unusable by any vehicle or person ((*12*) provides details).

Modeling Scenarios

The Base Scenario is the 2030 baseline forecast. The total households and firms are adapted from the households by age and employment projections from Metropolitan Area Planning Council (MAPC)'s Stronger Region Scenario.

The SLR_SHORT scenario represents the immediate transport response to inundation, assuming no change in trip destination or mode choice. The OD flow matrix by mode is fixed; lost trips are removed if they: 1) have travel times exceeding 180 minutes; or 2) are from/to inundated zones. For 1), we generate the travel time skims for the inundated network and apply the updated skim to select trips exceeding 180 minutes. For 2), if land in a zone is over 70% inundated (considered as "fully inundated"), all trips to/from that zone are 'lost'; otherwise, the share of zone's trips lost equals the zone's percentage of inundated area.

The SLR_LONG scenario models the long-term adaptation of land use and transport at four-foot inundation. This scenario contains several key assumptions. First, total households and firms remain the same. In other words, there is no inter-regional migration due to inundation. Second, we enforce a small upper bound (4 units) for the total supply of real estate units on all inundated TAZs (this was necessary for the land use model to converge). For the un-inundated TAZs, real estate supply has no upper bounds (no density constraint). In this way, we allow households and firms to freely move to anywhere but the inundated zones. Third, in the long run, a new real estate market equilibrium is reached.

IMMEDIATE INUNDATION IMPACTS

We first evaluate the immediate travel results in response to four-feet SLR, akin to the aftermath of a major storm surge. We examine two aspects: how many trips are lost because of extremely long travel times; then, given the remaining trips, how the road and transit networks perform compared to the base.

Lost Trips

In the 2030 base scenario, Greater Boston has 16.96 million trips, 14.6% of which (about 2.48 million) are lost due to inundation. As most inundated areas are located in the region's inner core with a high concentration of residents, jobs and educational institutions, we expect greater loss in Home-Based Work and Home-Based School trips. Table 1 shows that Home-Based Work and Home-Based School lose 19.7% and 21.3% trips, respectively, a greater percentage than for other trip purposes. Home-Based Shopping trips are least affected because of their generally lower trip length and local distribution pattern.

Our transport model distinguishes users into Choice and Captive groups based on household car ownership. Choice users' households have at least one car and have access to all modes; Captive user households do not own a car, and have no access to auto-related modes (SOV and DAT). We expect Captive users to have a greater share of lost trips due to their limited choice and transit's lower resilience under inundation. The model shows that Captive users lose 18.6% trips versus 13.7% for Choice users. Across all trip purposes, Captive users suffer a greater share of lost trips (Table 1).

The variations in lost trips across modes indicate different levels of resilience (Table 2). WAT and DAT have the highest percentages of lost trips, 51.7% and 94.2%, respectively. The broken connection on heavy rail, such as the Blue and Red Lines, forces transit users to switch to slower transit modes, such as bus, and make more transfers. Bus trips, moreover, are subject to roadway inundation impacts. Thus, transit trips are more prone to exceed the 3-hour travel time limit. The majority of the DAT destinations are in the inner-core area, thus suffering direct loss of trips. In contrast, WALK and SOV have the lowest shares of lost trips (7.8% and 9.9%), demonstrating the dense road networks' relative resiliency to inundation.

Road Network Performance

Network inundation has spillover effects, measured by the performance of un-inundated parts of the road network. After removing lost auto trips, the model assigns the remaining 90% auto trips to the road network. Table 3 summarizes traffic assignment results for the un-inundated part of the network. Vehicle-miles travelled (VMT) is an outcome of the number and distance of auto trips. Losing auto trips decreases VMT; while the deteriorated links cause travel detours, potentially increasing trip distances. Our model shows that average auto trip distance increases from 11 miles to 12 miles. The net change of VMT is -3%, compared to the -10% loss in auto trips. VMT by road link type suggests that local streets and main distributors play a key role in carrying detoured auto trips (Table 3).

Vehicle hours travelled (VHT) depends on the number of auto trips, trip distance and congestion. Despite fewer auto trips, travel detours increase auto trip distance, and increase congestion on un-inundated links. Average auto trip time increases from 19 minutes to 28 minutes; average auto speed decreases from 36 miles per hour to 13 miles per hour; and the 24-hour VHT increases by 173% -- clear signs of aggravated congestion.

Among the four periods of the day, PM peak experiences the largest increase in VHT (364%) relative to its baseline, followed by Mid-day (MD) (77%). Surprisingly, AM VHT increases only by 30%, less than MD. Similarly, PM average speed declines the most to 7 mph, followed by MD (21 mph). AM speed (27 mph) is even higher than MD. This is mostly because more AM VMT is on expressways relative to PM and MD (60% versus 56% and 55%, respectively). Since few expressways are inundated, the AM period is less affected by inundation. MD and PM VMT, on the other hand, accrues more on minor arterials, main distributors and local streets, which have lower speeds to begin with, suffer more inundation causing increased detours, and have lower capacity to accommodate more demand without increased congestion. This suggests that inundation's impacts vary across different times of day, depending on trip ODs at a given time, and how much the trips use inundated links.

The static traffic assignment procedure forces a small number of flows onto the inundated links. The deteriorated link capacity and free-flow speed make VHT on such links extremely high even with low volumes. Such travel can be considered 'lost' since realistically it cannot be completed.

Transit Ridership

The previous analysis shows that transit (WAT and DAT) loses 0.9 million trips (65%) of 1.4 million trips. Table 4 shows the ridership change for each transit mode. Rail experiences greater declines in ridership than bus or BRT. Bus and BRT ridership decreases by 42% and 65%, while Heavy Rail, Light Rail and Commuter Rail ridership declines by 70% to 89%.

Although total transit mode share is fixed in the short run, within transit mode shares can change due to each mode's changed skims. Basically transit ridership shifts from rail to bus. Bus share increases from 30% to 52%, while heavy rail's share drops from 38% to 26%. The shift reflects the relative flexibility and resilience of bus service. Bus service is more ubiquitous and has more route coverage (1595 miles) than rail (852 miles). The dense bus system can recover ridership from rail, a finding of particular interest for developing strategies for resilient transit systems.

LONG-TERM INUNDATION IMPACTS

Household and Firm Location Change

Figure 2 maps the changes in households and firms due to inundation at the TAZ level. Expectedly, inundated zones and their direct neighbors lose households. But some TAZs far from inundated areas also lose residents, partly due to decreased regional transit and/or auto accessibility. More interesting is the zones to which households move. New growth centers emerge on the peripheries of inundated zones, such as the southern part of Boston, western Somerville, Everett, Revere, Malden, and Lynn. Some regional urban centers, such as Lawrence in the north and Brockton in the south, experience significant household growth. These locations have high densities and a high concentration of low-income populations. The relatively low rents might be one of the factors attracting relocated households.

Comparing areas of household growth with the subway system location (Figure 2, left) does not show much correlation. New growth tends to locate in areas with good access to major highways (Figure 2, middle). These location observations support the model result that heavy rail ridership declines more in the long run than in the short run (as discussed later).

Table 5 summarizes household location changes by the Massachusetts Community Types, a classification system developed by the Metropolitan Area Planning Council (MAPC) (Figure 3). The Inner Core-Metro Core area experiences the largest decrease in households, since it contains the majority of the four-foot inundation area. This area has a net decrease of 98,609 households, 21% of its baseline value. Regional Urban Centers see the biggest growth in households, 65,407; some of these are not close to the inundated areas. Developing Suburbs have the second largest growth in households, 16,293.

The loss of firms mainly occurs in inundated areas. The Inner Core-Metro Core loses 44% of its firms, while in Inner Core-Streetcar Suburbs, Regional Urban Centers, Maturing Suburbs and Developing Suburbs the number of firms increases by 20% (Table 5). Firms favor locations with good highway access (Figure 2, right).

Long-term Transport Impact

Changes in transport supply and agent relocation work together to influence long-term travel outcomes. Vehicle ownership, modeled with sensitivity to land use and accessibility (*14*), increases, with the share of 0-vehicle households decreasing from 12% to 10% and households with 1 to 3+ vehicles modestly increasing. Two factors play a role: worsened transit service, especially rail, decreasing transit accessibility; and, location choices favoring auto-accessible places and encouraging car ownership.

Mode share is affected by trip distribution patterns and travel skims for each mode. For all trip purposes, SOV trips increase slightly, by 2%, while auto-passenger trips decrease by 1% (Table 6). For Home-based work trips, SOV share increases from 73% to 78%; for other trip purposes, SOV share stays almost the same. WAT and DAT trips decrease by 56% and 97%, respectively. Their mode shares decline for all trip purposes. WALK trips increase by 20%, increasing across all trip purposes. The substantial drop in transit share shows that transit is least resilient to network breakdown. The limited expansion in SOV share is probably due to worsened road congestion. The increased WALK trips compensate for lost transit trips. Average trip distances may decline, given a fixed travel time budget and higher travel impedances for auto and transit. The increasingly important role of WALK suggests that SLR may push people back to this traditional slow and flexible travel mode.

Long-term VMT declines by 4% compared to the base scenario (Table 3), somewhat counter-intuitive since total SOV trips increase by 2%. This implies that average auto trip distances become shorter. The model generates such results because in the trip distribution step, we fix the observed travel time distribution. Given an inundated network with higher overall travel times, trip distances must be shorter to make predicted travel time distributions match the observed. This may be a realistic assumption if people’s travel time budget remains fixed in the long run.

Short-run congestion largely diminishes in the long run, though it remains worse than the baseline. The long-term average auto travel speed (28 mph) is double the short-term (13 mph), yet still slower than the baseline (36 mph). Long-term VHT increases by 23%, a combined result of slightly increased auto trips, and worsened congestion. For each period of the day, road congestion nearly returns to baseline levels except for the PM peak (22 mph vs. 35 mph).

In the long-term SLR scenario, a small fraction of trips is still assigned to the inundated network, generating extremely high VHT. This is due to the nature of static assignment, which forces all trips within an hour window to load on the network, without limiting the Volume-Capacity Ratio. Nevertheless, very few links reveal this issue. Such links may serve a critical role in maintaining the network’s connectivity and serving key flows.

Transit ridership decreases more in the long run (-71%) than the short run (-66%). The most drastic ridership loss occurs in rail line services (-84% to -95%) relative to Bus’ 33% loss. Among transit services, Bus has the largest share of ridership in the long term (70%), compared to 30% in the Base Scenario.

CONCLUSIONS

We demonstrate the speculative use of an LUT model to forecast the short and longer term impacts of potential 4-foot SLR in Greater Boston. The short-term scenario represents the immediate transport system response to inundation, providing a measure of transport system resiliency in the case of an extreme event, such as a storm surge. The results show how transit captive users unsurprisingly will suffer more. Transit, in general, displays less resiliency, at least in part due to the center city’s vulnerability and Boston’s radial-focused transit system. Trip distances would modestly decrease, and average travel speeds would go down by over 50%. Rail transit ridership would be decimated and overall transit usage would go down by 66%.

The long-term scenario aims to predict how households and firms would prefer to relocate in the “new equilibrium” where over ten square miles of land disappear and the transport network inundations become permanent. Assuming no supply constraints, new residential growth centers would emerge on the peripheries of the inundated zones, primarily in the inner-core suburbs. Some regional urban centers, traditional industrial towns like Lowell and Lawrence, would boom. Firms would be hit harder in terms of relocation, due to their existing heavy concentration in the inner-core; firm relocation would largely follow households. Transit usage would again be decimated, but if there is a silver lining in the long-term forecast, walking would mostly make up for the transit loss, likely due to new sub-center formation and lack of investment in alternatives. This "doomsday" climate change scenario suggests human-powered travel, the quintessential low carbon mode, would rise again.

Naturally, these results need to be viewed with a heavy dose of skepticism and are not generalizable to other contexts. Our purpose was to demonstrate the possibilities of the tools, not produce forecasts for decision-making now. A range of shortcomings can be identified; we end with mentioning a few and implications for additional research. First, the models do not account for the highly likely uncertainty in behavior. The models assume people's preferences (for mobility, for housing, etc.) will remain the same, an unlikely assumption with or without SLR. In the long run scenario, we apply the same supply restriction to all inundated TAZs, regardless of the size of the inundated area; this will generate more relocation of households and firms. A more realistic approach would be to relate the constraints to the fraction of inundated area. We also assume no changes in firm or household population size, income levels or economic structures. On the transport modeling side, we used static traffic assignment, which can allow very high congestion on certain links, tending to overload the network; dynamic traffic assignment would generate more realistic and stable assignment results. The models ignore freight travel, which impacts system performance and firm location choices. In our application, we use mobility-focused performance metrics, while accessibility-based measures (e.g., *8*; *12*) may be more meaningful.

Finally, the scenarios, especially the long-term one, should not be mistaken for being "realistic." As the threat of SLR increases, infrastructures would most likely slowly adapt as would people, firms and the economy. The models used here could be used to help guide that adaptation, identifying which links or nodes should be reinforced, for example, and where new infrastructures may be necessary. The approach, refined, could in theory be used to identify areas most suitable for location, by different types of households and firms and to develop incentives to achieve a societally desirable, resilient LUT plan.

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REFERENCES

1. Orski, K. The Potential for Fuel Conservation: The Case of the Automobile. *Transportation Research*, Vol. 8, 1974, pp. 247-257.
2. Edwards, J.L. and J.L. Schofer. Relationships Between Transportation Energy Consumption and Urban Structure: Results of Simulation Studies. *Transportation Research Record 599*, 1976, pp. 52-59.
3. Donoso, P., F. Martínez, C. Zegras. The Kyoto Protocol and Sustainable Cities: The Potential Use of

the Clean Development Mechanism in Structuring Cities for “Carbon-Efficient” Transport. *Transportation Research Record 1983*, 2006, pp. 158-166.

4. National Research Council (NRC). *Potential Impacts of CLIMATE CHANGE on U.S. Transportation*. Transportation Research Board and Division on Earth and Life Studies, National Research Council of the National Academies, 2008.
5. Cambridge Systematics. Climate Change Vulnerability and Risk Assessment of New Jersey’s Transportation Infrastructure, 2012.
6. Bloetscher, F., L. Berry, J. Rodriguez-Seda, N. Hammer, T. Romah, D. Jolovic, B. Heimlich, M.A. Cahill. Identifying FDOT ’s Physical Transportation Infrastructure Vulnerable to Sea Level Rise. *Journal of Infrastructure Systems*, *20*(2), 2014, pp. 1–9.
7. Oswald, M., C. Treat. Assessing Public Transportation Vulnerability to Sea Level Rise: A Case Study Application. *Journal of Public Transportation*, Vol. 16, No. 3, 2013, pp. 59-77.
8. Lu, Q.-C. and Z.-R. Peng. Vulnerability Analysis of Transportation Network Under Scenarios of Sea Level Rise. *Transportation Research Record: Journal of the Transportation Research Board*, *2263*, 2011, pp. 174–181.
9. Suarez, P., W. Anderson, V. Mahal, T.R. Lakshmanan. Impacts of flooding and climate change on urban transportation: A systemwide performance assessment of the Boston Metro Area. *Transportation Research Part D: Transport and Environment*, *10*(3), 2005, pp. 231–244.
10. Chang, H., M. Lafrenz, I.-W. Jung, M. Figliozzi, D. Platman, C. Pederson. Potential Impacts of Climate Change on Flood-Induced Travel Disruptions: A Case Study of Portland, Oregon, USA. *Annals of the Association of American Geographers*, *100*(4), 2010, pp. 938–952.
11. Martínez, F.M. MUSSA: Land Use Model for Santiago City. *Transportation Research Record 1552*, 1996, pp. 126-134.
12. Dowd, M. 2015. Modeling Inundation Impacts on Transportation Network Performance: A GIS and Four-Step Transportation Modeling Analysis. Masters Thesis, Massachusetts Institute of Technology, Cambridge, 2015. http://dspace.mit.edu/handle/1721.1/99567.
13. Reardon, T. and M. Hari. Population and Housing Demand Projections for Metro Boston: Regional Projections and Provisional Municipal Forecasts. Metropolitan Area Planning Council, Boston, 2014. http://www.mapc.org/sites/default/files/MetroBoston%20Projections%20Final%20Report_1_16_2014_0.pdf
14. Han, Y. and C. Zegras. Exploring Model and Behavior Uncertainty: Temporal Transferability Assessment of Vehicle Ownership Models for Boston, Massachusetts, Metropolitan Area. *Transportation Research Record 2563*, 2016, pp. 122-133.

List of Tables and Figures

TABLE 1 Lost Trips by Purpose and by Choice and Captive Transit Users

	All riders			Choice			Captive		
	Base totals	Lost trips	% lost	Base totals	Lost trips	% lost	Base totals	Lost trips	% lost
HBW	3,001,273	-589,905	-19.7%	2,846,812	-555,026	-19.5%	154,462	-34,879	-22.6%
HBSH	1,777,807	-193,527	-10.9%	1,595,127	-159,553	-10.0%	182,680	-33,974	-18.6%
HBO	6,260,606	-835,059	-13.3%	5,848,881	-761,275	-13.0%	411,725	-73,783	-17.9%
NHBW	1,566,115	-204,866	-13.1%	1,499,609	-191,934	-12.8%	66,506	-12,932	-19.4%
NHBO	3,000,342	-371,271	-12.4%	2,783,589	-334,633	-12.0%	216,754	-36,638	-16.9%
HBSC	1,351,271	-287,616	-21.3%	---	---	---	---	---	---
Total	16,957,415	-2,482,244	-14.6%	14,574,018	-2,002,422	-13.7%	1,032,126	-192,205	-18.6%

Note: HBW: home-based work; HBSH: home-based shopping; HBO: home-based other; NHBW: non-home-based work; NHBO: non-home-based other; HBSC: home-based school.

TABLE 2 Lost Trips by Mode and by Trip Purpose

Mode		All Purposes	HBW	HBSH	HBO	NHBW	NHBO	HBSC
SOV	Base	8,196,419	2,194,269	883,702	2,810,049	937,497	1,370,902	----
	Lost	-810,705	-250,459	-75,100	-264,627	-88,296	-132,223	----
	% lost	-9.9%	-11.4%	-8.5%	-9.4%	-9.4%	-9.6%	----
APAX	Base	2,293,178	138,885	254,933	985,592	38,790	502,065	372,912
	Lost	-228,230	-17,708	-21,854	-92,356	-3,645	-45,432	-47,233
	% lost	-10.0%	-12.8%	-8.6%	-9.4%	-9.4%	-9.0%	-12.7%
WAT	Base	1,001,919	246,992	91,098	355,428	71,922	119,606	116,873
	Lost	-518,441	-143,669	-42,606	-168,505	-35,208	-61,325	-67,127
	% lost	-51.7%	-58.2%	-46.8%	-47.4%	-49.0%	-51.3%	-57.4%
DAT	Base	432,391	140,725	14,761	179,844	40,533	56,528	----
	Lost	-407,152	-134,458	-13,122	-168,103	-38,029	-53,440	----
	% lost	-94.2%	-95.5%	-88.9%	-93.5%	-93.8%	-94.5%	----
WALK	Base	4,632,950	280,402	533,313	1,929,693	477,373	951,241	460,928
	Lost	-362,149	-43,610	-40,845	-141,467	-39,687	-78,850	-17,688
	% lost	-7.8%	-15.6%	-7.7%	-7.3%	-8.3%	-8.3%	-3.8%

TABLE 3 Summary of VMT, VHT and Average Speed of Un-Inundated Road Links for Base Scenario and Sea Level Rise Scenarios

	VMT			VHT			Average Speed		
24Hour	**Base**	**SLR_ short**	**SLR_ long**	**Base**	**SLR_ short**	**SLR_ long**	**Base**	**SLR_ short**	**SLR_ long**
Expressways	52,146,971	-12%	-8%	977,197	15%	36%	53.4	41.0	36.3
Main Arterials	4,900,952	-23%	-24%	137,316	26%	-15%	35.7	21.8	32.0
Minor Arterials	17,098,101	-6%	-7%	633,380	49%	1%	27.0	17.1	24.9
Main Distributors	12,654,408	35%	16%	518,087	338%	32%	24.4	7.5	21.4
Minor Distributors	1,655,413	-9%	-7%	72,222	29%	25%	22.9	16.1	17.1
Local streets	4,552,634	27%	12%	231,230	939%	35%	19.7	2.4	16.3
Total	*93,008,479*	-3%	-4%	*2,569,432*	173%	23%	36.2	12.9	28.1
AM (hourly)									
Expressways	3,883,548	-12%	-6%	73,952	-4%	1%	52.5	48.1	48.9
Main Arterials	357,911	-31%	-27%	9,867	-13%	-22%	36.3	28.9	33.6
Minor Arterials	1,131,163	-9%	-3%	42,046	1%	0%	26.9	24.3	26.1
Main Distributors	783,261	35%	25%	32,293	105%	30%	24.3	16.0	23.2
Minor Distributors	115,897	-11%	-6%	5,191	16%	-4%	22.3	17.2	21.9
Local streets	259,739	40%	25%	13,213	175%	36%	19.7	10.0	18.1
Total	*6,531,519*	-5%	-2%	*176,562*	30%	7%	37.0	26.9	33.9
Mid-Day (hourly)									
Expressways	2,836,437	-9%	-10%	49,870	7%	-7%	56.9	48.7	55.5
Main Arterials	274,209	-25%	-26%	7,391	-20%	-23%	37.1	34.7	35.9
Minor Arterials	975,975	-5%	-9%	35,459	17%	-8%	27.5	22.3	27.2
Main Distributors	734,671	29%	11%	29,786	145%	13%	24.7	13.0	24.0
Minor Distributors	93,368	-10%	-10%	3,971	15%	-8%	23.5	18.4	23.1
Local streets	275,172	21%	9%	13,894	404%	10%	19.8	4.8	19.5
Total	*5,189,832*	-2%	-7%	*140,371*	77%	-2%	37.0	20.5	35.3

TABLE 3 (continued)

	VMT			VHT			Average Speed		
PM (hourly)	**Base**	**SLR_ short**	**SLR_ long**	**Base**	**SLR_ short**	**SLR_ long**	**Base**	**SLR_ short**	**SLR_ long**
Expressways	5,158,785	-14%	-7%	103,947	39%	91%	49.6	30.7	24.2
Main Arterials	480,774	-22%	-22%	14,421	82%	-5%	33.3	14.2	27.5
Minor Arterials	1,699,531	-5%	-7%	64,831	113%	11%	26.2	11.7	22.1
Main Distributors	1,290,045	43%	17%	53,512	693%	52%	24.1	4.4	18.5
Minor Distributors	162,680	-10%	-5%	7,385	58%	70%	22.0	12.6	12.3
Local streets	459,305	29%	9%	23,582	2012 %	61%	19.5	1.2	13.2
Total	*9,251,120*	-2%	-3%	*267,678*	364%	55%	*34.6*	7.3	21.5
Rest of Day (hourly)									
Expressways	1,418,985	-8%	-10%	23,743	-8%	-11%	59.8	59.4	60.2
Main Arterials	135,187	-16%	-22%	3,482	-15%	-20%	38.8	38.2	38.1
Minor Arterials	497,320	-5%	-9%	17,693	-1%	-9%	28.1	27.0	28.1
Main Distributors	367,554	23%	11%	14,725	30%	12%	25.0	23.6	24.9
Minor Distributors	47,112	-7%	-8%	1,899	-1%	-8%	24.8	23.3	24.6
Local streets	138,835	16%	8%	6,948	62%	8%	20.0	14.3	19.9
Total	*2,604,993*	-2%	-6%	*68,490*	9%	-4%	38.0	34.0	37.0

TABLE 4 Transit Ridership by Transit Mode of Base and SLR Scenarios

	Transit Trips			Percentage change in trips		Transit Mode Share		
Transit Mode	**Base**	**SLR_ SHORT**	**SLR_ LONG**	**SLR_ SHORT**	**SLR_ LONG**	**Base**	**SLR_ SHORT**	**SLR_ LONG**
Bus	785,391	458,077	530,352	-41.7%	-32.5%	30%	52%	70%
BRT								
Silver line	52,901	18,774	2,722	-64.5%	-94.9%	2%	2%	0%
Heavy Rail	989,239	225,584	138,144	-77.2%	-86.0%	38%	26%	18%
Red line	453,706	67,236	84,672	-85.2%	-81.3%	17%	8%	11%
Orange line	428,833	149,495	53,172	-65.1%	-87.6%	16%	17%	7%
Blue line	106,700	8,853	300	-91.7%	-99.7%	4%	1%	0%
Light Rail								
Green line	478,954	141,962	77,225	-70.4%	-83.9%	18%	16%	10%
Commuter Rail	305,129	33,288	17,333	-89.1%	-94.3%	12%	4%	2%
Total	2,611,615	877,685	765,777	-66.4%	-70.7%	100%	100%	100%

TABLE 5 Changes in Household Location and Firm Location by Community Types

	Number of Households				Number of Firms			
	Base	SLR	Diff	% Diff	Base	SLR	Diff	% Diff
Inner Core-Metro Core	468,060	369,451	-98,609	-21.1%	10,281	5,790	-4,491	-43.7%
Inner Core-Streetcar Suburbs	207,586	215,824	8,238	4.0%	2,555	3,073	518	20.3%
Regional Urban Centers	477,767	543,174	65,407	13.7%	6,806	8,167	1,361	20.0%
Maturing Suburbs	473,149	481,821	8,672	1.8%	7,457	8,971	1,514	20.3%
Developing Suburbs	408,010	424,303	16,293	4.0%	5,278	6,377	1,098	20.8%

TABLE 6 Trips by Mode and Mode Shares by Trip Purpose: Base vs. SLR Long-term Scenario

	Total Trips by Mode			Mode Shares by Trip Purpose									
				HBW		HBSHOP		HBO		NHBW		NHBO	
	Base	SLR_LONG	diff in %	Base	SLR	Base	SLR	Base	SLR	Base	SLR	Base	SLR
SOV	8,196,417	8,362,324	2.0%	73%	78%	50%	49%	45%	45%	60%	60%	46%	45%
APAX	1,920,264	1,900,066	-1.1%	5%	4%	14%	14%	16%	16%	2%	2%	17%	16%
WAT	885,044	387,253	-56.2%	8%	4%	5%	2%	6%	2%	5%	2%	4%	2%
DAT	432,389	11,564	-97.3%	5%	0%	1%	0%	3%	0%	3%	0%	2%	0%
WALK	4,172,020	4,994,889	19.7%	9%	13%	30%	35%	31%	37%	30%	36%	32%	37%
Total	15,606,134	15,656,096		100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

Note: SOV: single-occupant vehicle; APAX: auto passenger; WAT: walk-access transit; DAT: drive-access transit; WALK: walk

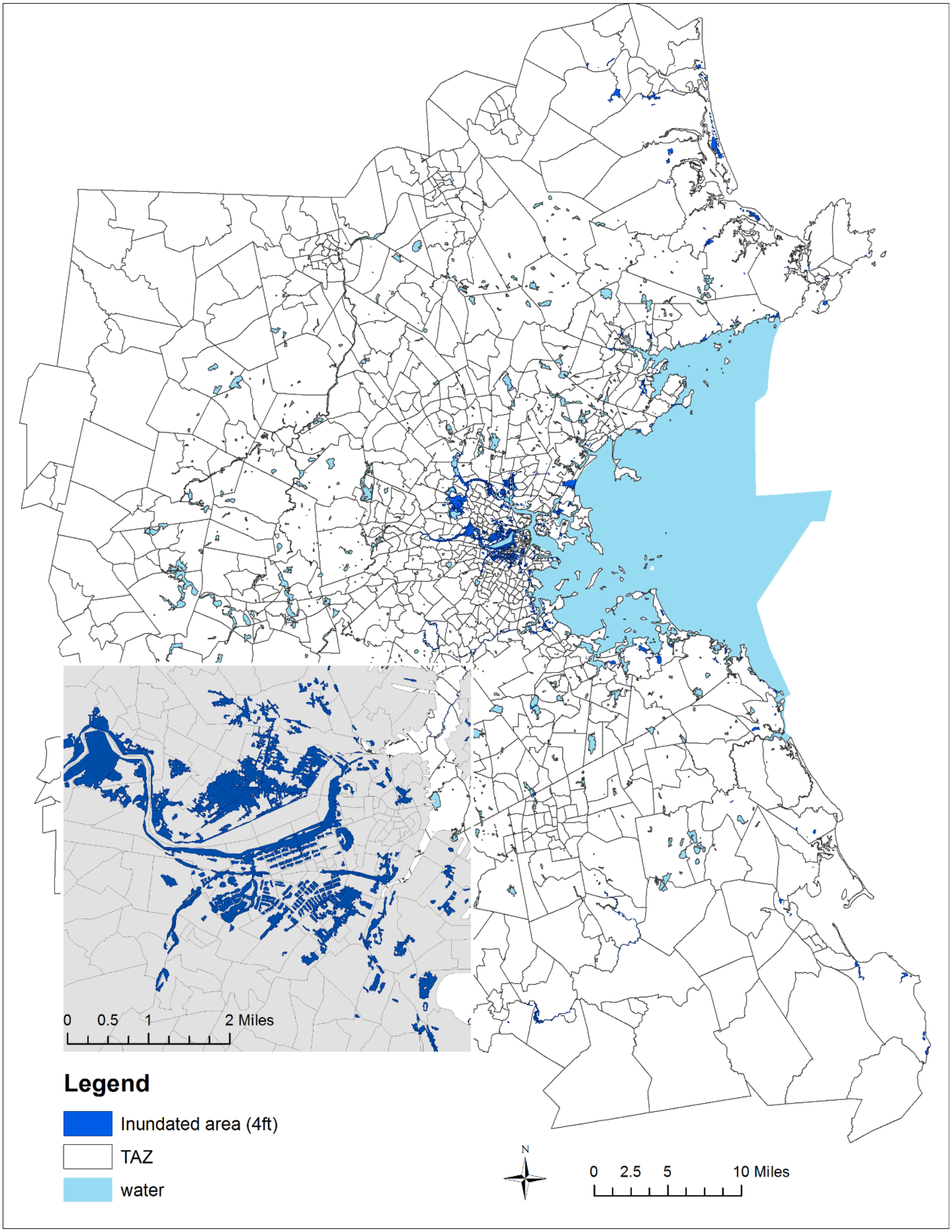

FIGURE 1 Four-foot sea level rise inundation area.

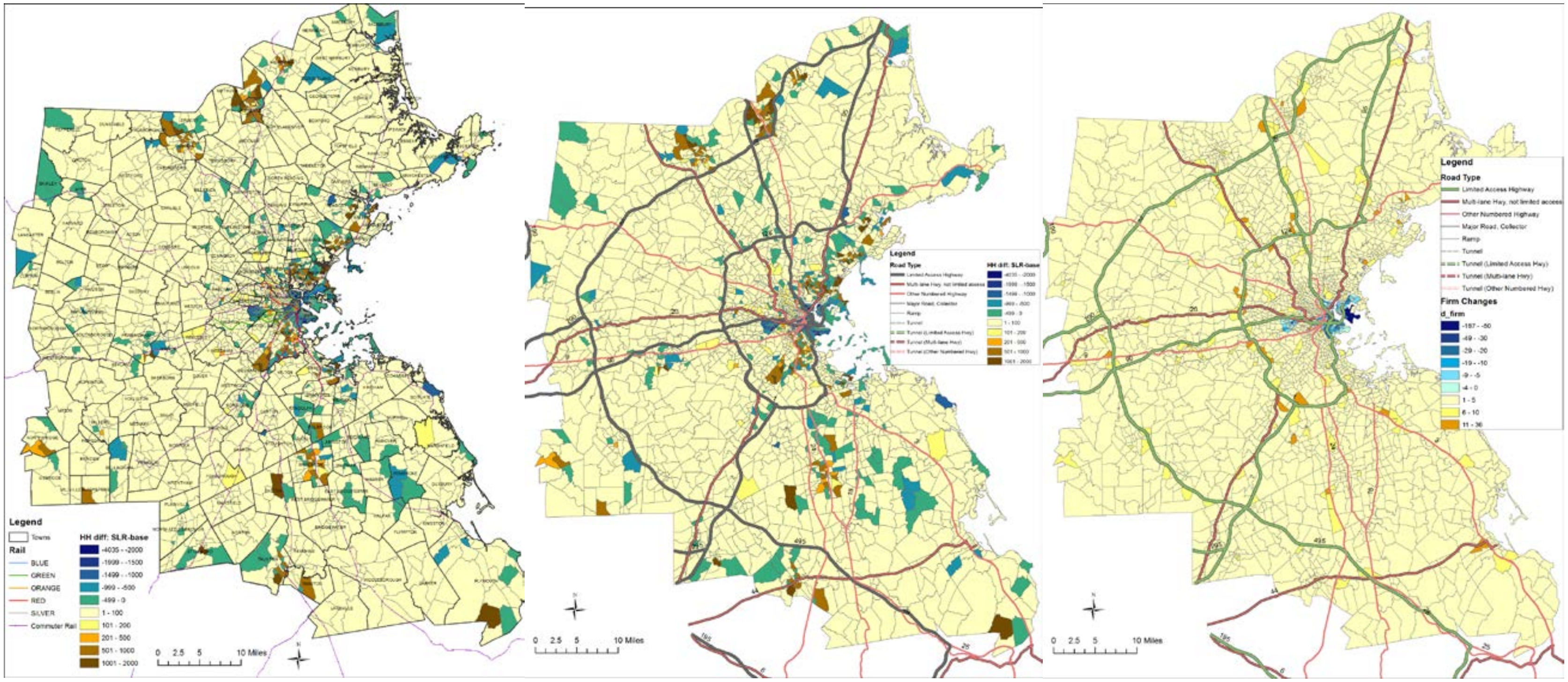

FIGURE 2 Predicted changes in locating agent by TAZ at four-foot inundation rise (left, households with major transit network shown; middle, households with highways shown; right, firms with highways shown).

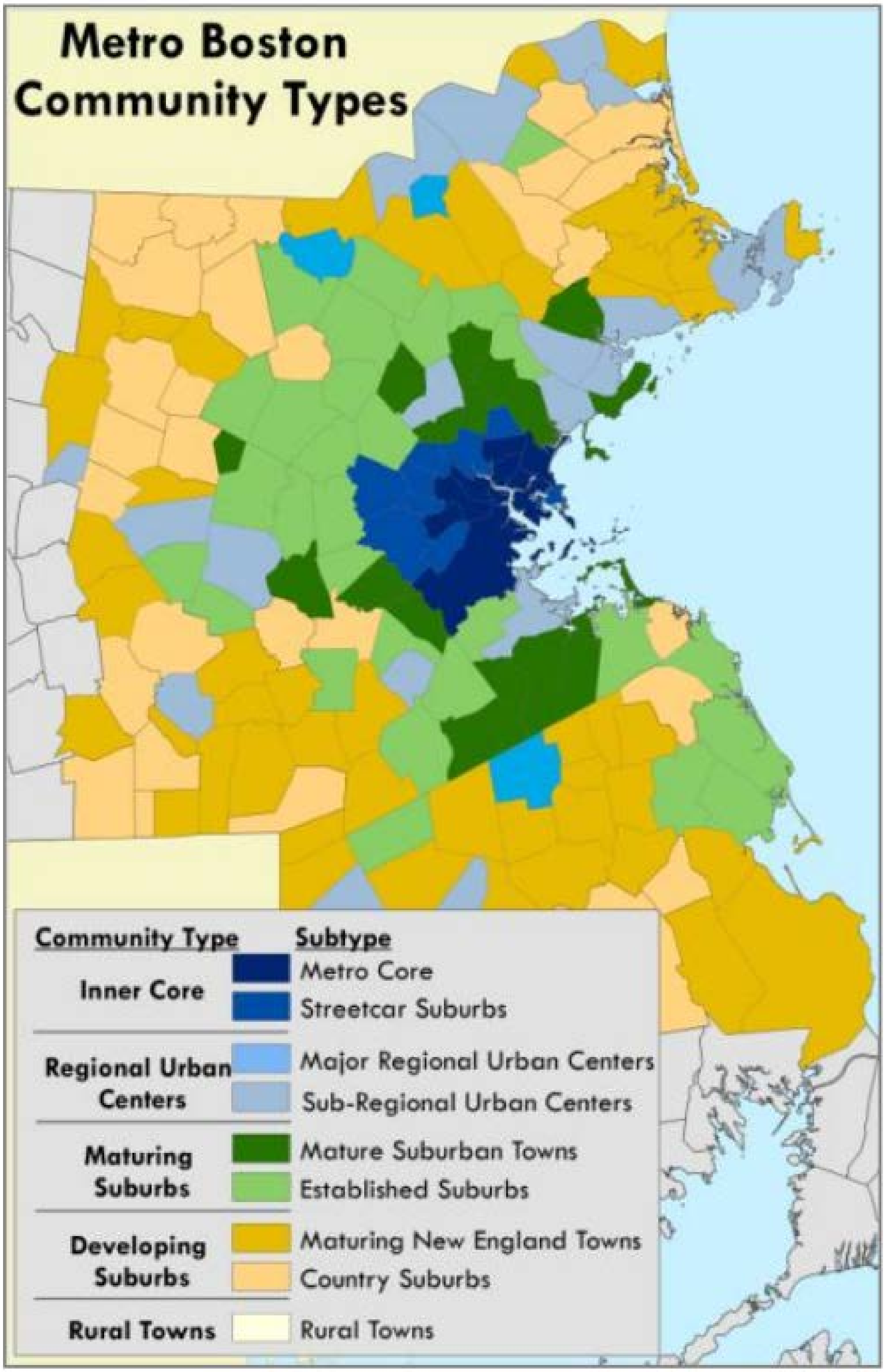

FIGURE 3 Community type of the model area.
Source: (*13*)